A Video Recommendation Algorithm Based on Hyperlink-Graph Model

Songtao Shang, School of Computer Science, Communication University of China, Beijing, China
Wenqian Shang, School of Computer Science, Communication University of China, Beijing, China & Beijing Key Laboratory of Big Data in Security & Protection Industry, Beijing, China
Minyong Shi, School of Computer Science, Communication University of China, Beijing, China
Shuchao Feng, School of Science, Communication University of China, Beijing, China
ZhiGuo Hong, School of Computer, Faculty of Science and Engineering, Communication University of China, Beijing, China

ABSTRACT

The traditional graph-based personal recommendation algorithms mainly depend on the user-item model to construct a bipartite graph. However, the traditional algorithms have low efficiency, because the matrix of the algorithms is sparse and it costs lots of time to compute the similarity between users or items. Therefore, this paper proposes an improved video recommendation algorithm based on hyperlink-graph model. This method not only improves the accuracy of the recommendation algorithms, but also reduce the running time. Furthermore, the Internet users may have different interests, for example, a user interest in watching news videos, and at the same time he or she also enjoy watching economic and sports videos. This paper proposes a complement algorithm based on hyperlink-graph for video recommendations. This algorithm improves the accuracy of video recommendations by cross clustering in user layers.

KEYWORDS

Bipartite Graph, Cross Clustering, Hyperlink-Graph, Video Recommendation

1. INTRODUCTION

Online video is becoming more popular in recent years. Many people, especially young teenagers, are more likely to watch online videos through mobile devices. By the end of June 2016, the online video users have reached 514 million in China. Therefore, the most important problem for online users is how to find their favorite videos, and for commercial video websites is to recommend an appropriate online program to a certain user. Personal recommendation system (Alhamid, Rawashdeh & Dong et al., 2016) can help predict the interest or preference of a certain user, for particular item. In recent years, personalized recommendations have become an essential service for commercial websites. Comparing with the booming e-commerce website, the service level of personalized recommendations still falls behind. Hence, in this paper, we propose a recommendation system, that is, personalized video recommendation system. This system help Internet users find their favorite videos automatically.

Up to now, there are various kinds of algorithms for personalized recommendations (Yang & Zhao, 2011). Most of these algorithms can be roughly divided into four categories, that is, content-based (Lops, Gemmis & Semeraro, 2011), graph-based (Shao & Chen, 2009), collaborative filtering-based (Su & Khoshgoftaar, 2009; Zhang, 2009) and hybrid recommendation algorithms (Lucas, Luz, Moreno et al., 2013).

DOI: 10.4018/IJSI.2017070104

Copyright © 2017, IGI Global. Copying or distributing in print or electronic forms without written permission of IGI Global is prohibited.
Content-based recommendation algorithms need to construct user preference model through analyzing user’s browsing behavior and calculating the similarity between recommendation items and user preference items. The most similar item will be recommended to the corresponding user. The basic assumption of the recommendation algorithms based on collaborative filtering (Cao, 2013) is: recommending interest items for users can find other users who have similar preferences. The collaborative filtering can be divided into two kinds: memory-based collaborative filtering (Melville, Mooney & Nagarajan, 2006) and model-based collaborative filtering (Deshpande & Karypis, 1998; Breese, Heckerman & Kadie, 2013).

The graph-based algorithm for personalized recommendation mainly constructs a bipartite graph (Aggarwal, Wolf, Wu et. al., 1999; Feldman & Sanger, 2007; Abel, Henze & Krause, 2008) based on the user-item model. Zhou et al. (2007, 2008) construct a bipartite graph algorithm based on resource allocation matrix and random walks (Fancois, Alain, Marco et al., 2007; Shang, Kulkami, Cuff et al., 2012) to realize personalized recommendations. But their overhead of computation and storage is the most. Zhang et al. (2009) present a hybrid graph model with two layers for personalized recommendations based on a small world network and a Bayesian network (Watts & Strogatz, 1998). Their algorithms can get a good recommendation result, but it is easy to lead to a Non-Polynomial-hard (NP-hard) problem.

The improved video recommendation algorithm, proposing in this paper, based on the hyperlink-graph model, can acquire better personalized video recommendations for users by introducing ordered nodes of hyperlinks. It is a hybrid algorithm that aims to overcome the shortcomings of content-based, collaborative filtering, and graph-based recommendation algorithms. We also propose a complementary algorithm in this paper. This algorithm improves the recommendation accuracy of multiple interest users by introducing cross clustering for users.

2. CLASSICAL GRAPH-BASED RECOMMENDATION ALGORITHM

The classical graph-based recommendation algorithm (Li, Su & Wang, 2012) mainly depends on constructing a resource allocation matrix over a graph and following the random walk algorithm. The detailed description is as follows:

Step 1. Build a bipartite graph. Assume that there are $U$ users and $N$ videos in the recommendation system. The system can be expressed by a $U+N$ nodes bipartite graph. It can be described as Figure 1.

Construct the metric matrix. This process includes two parts. One is resource allocation from videos to videos. The other is resource allocation from user to videos. The resource allocation weight $\omega_{ij}$ from video $j$ to user $i$ can be described as follows:

$$\omega_{ij} = \frac{1}{D_j} \sum_{k=1}^{U} \frac{a_{ik}a_{jk}}{D_k}$$

(1)

where, $D_j$ means how many users browse $j$. $D_k$ is the number of videos that user $k$ has ever browsed. Hence, the metric matrix is a square matrix $D = (\omega_{ij})_{N \times N}$.

Step 3. For target user, we need to decide his/her initial resource allocation vector. It is denoted by $f_u = (a_{1u}, a_{2u}, \ldots, a_{ju}, \ldots, a_{Nu})$. If user $u$ has browsed video $j$, then $a_{ju} = 1$; otherwise $a_{ju} = 0$. The resource allocation vector is 0/1 vector. The ultimate resource allocation vector can be described as follows:
Agent-Development Framework Based on Modular Structure to Research Disaster-Relief Activities
[www.igi-global.com/article/agent-development-framework-based-on-modular-structure-to-research-disaster-relief-activities/210451?camid=4v1a](www.igi-global.com/article/agent-development-framework-based-on-modular-structure-to-research-disaster-relief-activities/210451?camid=4v1a)

Capacity-Driven Web Services: Concepts, Definitions, Issues, and Solutions
*Theoretical and Analytical Service-Focused Systems Design and Development* (pp. 392-415).
[www.igi-global.com/chapter/capacity-driven-web-services/66810?camid=4v1a](www.igi-global.com/chapter/capacity-driven-web-services/66810?camid=4v1a)